

Optimizing Deep Learning Algorithm for Tears Sensor Data Analysis: An Algorithmic Analysis

Dr. Sarbeswar Hota^{1*}, Dr. Abhiraj Malhotra², Dr.R. Hannah Jessie Rani³,
Dr. Vijay Jagdish Upadhye⁴, Prateek Aggarwal⁵, and Dr. Awakash Mishra⁶

^{1*}Associate Professor, Department of Computer Applications, Siksha 'O' Anusandhan (Deemed to be University), Bhubaneswar, Odisha, India. sarbeswarahota@soa.ac.in, <https://orcid.org/0009-0006-0921-8323>

²Centre of Research Impact and Outcome, Chitkara University, Rajpura, Punjab, India. abhiraj.malhotra.orp@chitkara.edu.in, <https://orcid.org/0009-0005-1871-4807>

³Department of Electrical and Electronics Engineering, Faculty of Engineering and Technology, JAIN (Deemed-to-be University), Bangalore, Karnataka, India. jr.hannah@jainuniversity.ac.in, <https://orcid.org/0000-0002-5449-104X>

⁴Department of Microbiology, Research and Development Cell, Parul University, Vadodara, Gujarat, India. vijay.upadhye82074@paruluniversity.ac.in, <https://orcid.org/0000-0002-8821-1720>

⁵Chitkara Centre for Research and Development, Chitkara University, Himachal Pradesh, India. prateek.aggarwal.orp@chitkar.edu.in, <https://orcid.org/0009-0001-8154-6018>

⁶ Professor, Maharishi School of Engineering & Technology, Maharishi University of Information Technology, Uttar Pradesh, India. awakash.mishra@muit.in, <https://orcid.org/0009-0009-8318-950X>

Received: May 06, 2025; Revised: June 24, 2025; Accepted: August 11, 2025; Published: September 30, 2025

Abstract

There have been significant developments in deep learning-based algorithms in various domains, including healthcare. One aspect that may benefit from diagnostics and monitoring is tear sensor data. Nevertheless, conventional data analysis methods struggle with extracting what is meaningful from tear sensor data, which are complex and high-dimensional. In the present study, we introduce a novel deep-learning model for the efficient analysis of tear sensor data. To process the data from the tear sensors, we employ sophisticated machine learning algorithms, such as Convolutional and Recurrent Neural Networks, for feature extraction and pattern recognition in our algorithm. Specifically, we employ a novel data preprocessing method to reduce noise and enhance data quality substantially. Improved methods, such as the one described above, yield more rapid and accurate analysis of tear sensor data as well as enhanced disease detection and monitoring.

Keywords: Deep Learning, Healthcare, High-Dimensional, Preprocessing Technique, Disease Detection, Monitoring.

Journal of Wireless Mobile Networks, Ubiquitous Computing, and Dependable Applications (JoWUA), volume: 16, number: 3 (September), pp. 27-48. DOI: 10.58346/JOWUA.2025.I3.002

*Corresponding author: Associate Professor, Department of Computer Applications, Siksha 'O' Anusandhan (Deemed to be University), Bhubaneswar, Odisha, India.

1 Introduction

It stands for analyzing tear microsensor data using algorithms. This post assumes tears are full of juicy information about our health (both emotional and physical) (El Barche et al., 2024). Diabetic Care, Engineering Data Analytics, Flame Sensors, Multicore Processor, Tear Composition, Tear Production, Tear Quantity, Tear Quality, Data Analytics, Data Analysis, Wireless Sensors, Wearable Sensors, Power Management, Re-Id, Privacy, Medical Privacy 4 Algorithmic Analysis Throughout this disclosure, the term "algorithmic analysis" is used to describe the mathematical and/or computer-implemented method employed to process and interpret data collected by a variety of sensors that measure in or near a person's tear (Sethi & Soman, 2022). The algorithms we aim to handle in this paper are those that mine patterns, relationships, and trends within the data and report them back to the emotional and physical state of a person (Lee et al., 2021). This type of analysis aims to be less personal and more quantifiable with respect to one's condition, both emotionally and physically, compared to conventional self-reporting, which can often be heavily influenced by bias and is entirely subjective. Reading the tears sensor data in several steps, data from the tears sensor (Alonso-González et al., 2023) is shown. The sensors then monitor the volume, flow rate, and chemical composition of the tears. This raw data is preprocessed to remove any noise or artifacts in a manner that ensures our analysis is conducted on high-quality, definitive data (Amethiya et al., 2022). The challenge revolves around sensor data that detects tear production and tear composition in the eye, and the solution is an algorithm. This is important because it indicates the health of someone's tear film, which is vital for maintaining healthy eyes (Tan et al., 2024). However, there are multiple potential problems with this analysis, which can negatively impact the validity and repeatability of the results (El Barche et al., 2024). Data Collection: One conceivable issue involves issues associated with data collection. Sensor data analysis, specifically the measurement of tear production or tear composition, is crucial to many computational health measures; however, these measures are prone to being inaccurate or imprecise. Mistakes in data recording, such as using sensors that are no longer functioning or have been tampered with in advance, can result in an incorrect estimation (Ho et al., 2022). It is critically important, then, to take great care in recording the data to minimize the risk of such errors. Furthermore, it is about the complexity of analyzing the various distributions of the data. Tear sensor data analysis involves the examination of a large dataset of data points collected by a network of sensors located in or around specific areas. Such a technique may be slow and tedious if the drug has multiple parameters to determine (Odimarha et al., 2024). Effective handling of the data in this problem is necessary to employ practical algorithms and powerful computing systems, such as those used in robust settings (Selvaraj & Selvaraj, 2022). Tear composition and its production may be altered due to external influences (such as environmental conditions, diet, and medications). These disparities may negatively impact the accuracy of the results, and additional methods are often required to address them. These sensors are also presumably limited due to their insensitivity to certain analytes (e.g., PG) or the relative specificity of individual tear components (Sun et al., 2023). This may also bias the result and could require further verification methods. Tears Sensor Data Analysis is Tears (TRS) Data Interpretation, which involves making sense of the data and ultimately interpreting it. Analysis algorithms should be tailored to a specific situation, taking into account the patient's age and sex (Zhao et al., 2024). Ignoring all these factors is an easy path for a patient to find their interpretation and diagnosis. 5. Conclusions: There are numerous challenges and problems in analyzing tear sensor data. To improve the results, the development of algorithms and sensor technology is necessary to obtain stable and accurate data. Here are the key contributions of the paper,

- Tear sensor data analysis algorithm: This paper proposes a high-accuracy and efficient tear sensor data analysis algorithm. The tools can analyse large quantities of data quickly and may be beneficial for researchers and clinicians who study tears.
- Critical parameters for identifying tear sensor data: The tear sensor data may vary due to several parameters, such as blinking, eye movement, and sensor position, which have all been considered in the proposed algorithm presented in this paper. Abstract Background Compared to other biofluids, tear information is far more extensive, enabling further understanding of the underlying physiological processes and underlining the potential of tears as a diagnostic and monitoring tool.
- Future perspectives in tear analysis: In the future, the algorithm developed in the present study, after optimization, can be used for various applications related to tear analysis, such as dry eye disease diagnosis, contact lens comfort testing, and tear film stability examination

The rest of the work is organized as follows. A discussion of recent related works is presented in Chapter 2. Chapter 3 presents the model, and Chapter 4 presents the comparative study. Chapter 5 presents the results, and Chapter 6 discusses the conclusions and future work of the research.

2 Related Words

Mousavizadegan et al., (2023) This article has provided an account of Machine learning in analytical chemistry. The implementation of machine learning in analytical chemistry aims to process large amounts of data by using artificial intelligence algorithms to discover patterns and make predictions, thereby enhancing precision and efficiency in chemical analysis. This strategy has been extended to fabricate nanostructures and for sensing applications involving luminescence. Abidi et al., 2022 propose predictive maintenance planning for Industry 4.0, which involves ranking the machine learning models utilized by analyzing data produced by manufacturing and matching the results to generate forecasts. Utilizing these approaches, businesses can save time, avoid downtime, and eliminate costly maintenance and repair expenses (Sherlin & Nikila 2022; Sherlin & Nikila, 2022). It has the potential to result in greener production and a more robust production system. (Sircar et al., 2021) note that the application of Machine learning and artificial intelligence in the oil and gas industry for enhancing efficiency, safety, and decision-making is becoming increasingly common. These technologies can process and interpret massive amounts of data to improve drilling and production efficiencies, as well as forecast machinery breakdowns and potential hazards.

Garaszczuk et al., 2024 have described how machine learning enables contact lens practitioners to confidently predict tear osmolarity, a key measurement in eye health. After running the data through various factors, such as tear generation and environmental conditions, machine learning can ultimately make predictions on the best contact lens type for a patient. (Wang et al., 2023) have reviewed artificial intelligence sensors, more sophisticated technologies based on AI algorithms, and machine learning methods for processing and interpreting healthcare and biomedical sensor data. These techniques enable the creation of the next generation of treatment platforms, which measure and treat diseases accurately in real-time, thereby achieving patient recovery and healthcare efficiency.

Zhang et al., 2022 have briefly explained how Machine learning has transformed well-sensing well-sensing electronic systems by enhancing the performance of the SEAN algorithm, which is trained on big data. AI systems can predict and analyze historical and real-time data more accurately, enabling them to be more timely and valuable. Machine learning has been applied to the development of intelligent and personalized devices for various applications, including health and activity monitoring.

Kumar et al., 2021 have described a genetically based optimized Fuzzy C-means data clustering method, which utilizes genetic algorithms to determine the optimal parameters for the Fuzzy C-means clustering algorithm. This is demonstrated using real-world IoMT data to identify biomarkers for the fast and accurate detection of affective states in bright-edge data analytics. (Xue et al., 2024) have described how expert-level accuracy in differentiating ACL tear types on MRI can be achieved nowadays, thanks to the evolution of deep learning methods. The combination of convolutional neural networks with another deep learning algorithm has the potential to discriminate between different types of ACL tears successfully; this promising approach makes diagnosis and treatment planning more effective and efficient.

Ngwa & Ngaruye, (2023) have discussed big data analytics for predictive system maintenance, which leverages machine learning models on large datasets to identify clusters and trends that can help predict when maintenance is needed on the system. It allows for better problem addressing by eliminating the need for monitoring and maintenance windows, resulting in fewer downtime delays and lower costs. Pandey, (2021) have addressed how ML can be used to be integrated into mechatronic systems for predictive maintenance. These Convolutional Neural Networks algorithms process system data and predict possible failures or MALFs before they occur (Binny & Maran, 2025). This may help with maintenance planning and downtime, as well as make the system more dependable and efficient.

Shimizu et al., (2023) have described Information visualization and machine learning as emerging techniques in impedimetric biosensing, a technique used to detect and analyze biomolecular interactions. These strategies employ more robust data analysis and visualization schemes to process and interpret impedance measurements, allowing for the sensitive extraction of relevant information. This enhances biosensing accuracy and sensitivity across a wide range of applications, including biomedical diagnostics and drug discovery. Djeddi et al., (2022) has proposed that Gas turbine availability improvement can be studied using short-term memory networks and deep learning methods applied to historical turbine failure data. This may help predict patterns and anticipate potential failures, thereby facilitating preventive maintenance and reducing unscheduled downtime, which in turn can lead to higher availability and performance of gas turbines.

Yang et al., (2021) have described How Computer vision technology has been more useful in the sensing process of blast furnace bearings and possible threat inference technology, among which hybrid deep learning algorithms are used to analyze and detect abnormal vibrations, temperatures, etc. Computer vision-based tool offers live monitoring capabilities and provides early warnings of potential problems, enabling safer and more effective operation of the industrial process. Kim et al., (2023) have reported an indolizine-based fluorescence compound array for detecting and monitoring glucose levels in biofluids (Boopathy et al., 2024; Boopathy et al., 2024). Computer vision incorporates on-device machine learning to interpret the compounds' fluorescence patterns and accurately measure glucose levels (Albert Mayan et al., 2025; Albert Mayan et al., 2025). This makes it possible to monitor the level of glucose in the body in a non-invasive and accurate manner. Zhang et al., (2024) discussed the method of combining a convolutional neural network (CNN) and a modified golden search algorithm for accurate diagnosis of anterior cruciate ligament (ACL) tears. The CNN is developed using MRI normal and tear ACL images and is optimized using the modified golden search algorithm for improved performance Table 1.

Table 1: Comprehensive Analysis

Authors	Year	Advantage	Limitation
Mousavizadegan et al., 2023	2023	Using machine learning allows for quick and accurate analysis of large amounts of data, improving the efficiency and accuracy of analytical chemistry research.	Limited availability of labeled training data and difficulty in interpreting complex models for understanding underlying chemistry principles.
Abidi et al., 2022	2022	Improved equipment reliability and reduced maintenance costs through real-time monitoring and detection of potential failures using accurate machine learning algorithms.	Lack of historical data or inaccurate data can lead to incorrect predictions and hinder maintenance decisions in highly complex systems.
Sircar et al., 2021	2021	Streamlined decision making and improved operational efficiency through automated data analysis and predictive maintenance.	One limitation could be the high costs associated with implementing and maintaining these advanced technologies.
Garaszczuk et al., 2024	2024	Machine learning-based prediction can provide more accurate and personalized tear osmolarity readings for improved contact lens fitting and management.	Difficulty in accurately predicting osmolarity due to individual variations in tear composition and contact lens characteristics.
Wang et al., 2023	2023	Increased accuracy and efficiency in monitoring and diagnosing medical conditions, leading to better patient outcomes and reduced healthcare costs.	One limitation could be the high cost of implementing and maintaining these technologies, which may limit their accessibility to certain populations.
Zhang et al., 2022	2022	Higher accuracy and reliability in data processing and analysis, leading to improved usability and functionality of wearable devices.	Overfitting to specific data sets can result in reduced accuracy when applied to different scenarios or users.
Kumar et al., 2021	2021	Improved accuracy in identifying affective states allows for more efficient and personalized healthcare interventions for individuals using IoMT technologies.	One limitation is that the accuracy of the clustering may be affected by the quality and quantity of the biomarker data.
Xue et al., 2024	2024	The deep learning model can effectively differentiate between different types of ACL tears with high accuracy, leading to improved diagnosis and treatment plans.	The algorithm may not perform well on MRI images with poor resolution, noise, or other forms of visual artifact.
Ngwa & Ngaruye, 2023	2023	Improved accuracy in predicting equipment failures allows for timely maintenance and reduces overall downtime, increasing productivity and cost savings.	The accuracy of predictive models is limited by the quantity and quality of data available for training the machine learning algorithms.
Pandey, 2021	2021	Improved accuracy in predicting equipment failures, allowing for more timely and efficient maintenance and reducing downtime and costs.	Limited training data and difficulty in adapting to changing system conditions leading to unstable or inaccurate predictions.
Shimizu et al., 2023	2023	Integration of advanced machine learning algorithms can improve accuracy and detection limits of biosensors, revolutionizing disease diagnosis and tracking trends.	Information visualization and machine learning methods rely on historical data, limiting their ability to detect new and novel biomarkers or patterns.

Djeddi et al., 2022	2022	Quicker identification of potential failures and proactive maintenance, resulting in higher efficiency and reduced downtime.	Lack of a large and diverse dataset can limit the accuracy and generalizability of the predictive capabilities of the LSTM model.
Yang et al., 2021	2021	Maximizes accuracy of detection, reducing false alarms and improving overall security and safety of the blast furnace operations.	Limited ability to detect anomalies if the training data is not representative of all potential scenarios.
Kim et al., 2023	2023	High sensitivity and selectivity towards glucose detection in bio-fluids, resulting in accurate and real-time monitoring of blood sugar levels.	Limited sensitivity and specificity could result in inaccurate glucose measurements, impacting overall reliability and effectiveness of the method.
Zhang et al., 2024	2024	Enhanced accuracy in diagnosis, leading to better treatment outcomes and improved patient care.	Limited to images of anterior cruciate ligament tears, may not be applicable to other types of knee injuries or issues.

- **Data Collection Unreliability** – The data weighted from the tears sensor may be unreliable due to consistency issues in data collection, which may lead to either a lack of data or inaccurate data. This may occur as a result of device malfunction, misplacement on the eye, miscalibration, or the like.
- **No standardized measurements:** the measurement of tears sensor data must be better standardized, as this makes comparisons difficult. This may be a result of differences in sensor placement, fluid collection methods, or data analysis techniques.
- **Intervention of External Factors:** External influences, such as environmental factors or eye movements, can interfere with tear sensor measurement and analysis, potentially leading to a misleading diagnosis.
- **One problem is algorithmic efficiency in deep learning.** While deep learning models have shown promising results across numerous domains, training and fine-tuning them is generally computationally expensive and time-consuming. However, there are some very recent studies that aim to improve deep learning and obtain efficient models by progressing in new directions. Adaptive learning rates represent one of the significant technical advances in this field. Dynamically scaled learning rates characterize this strategy according to in-data features, offering additional benefits, including faster training and improved overall performance. In a similar vein, several approaches have rigorously explored optimization procedures (e.g., gradient descent or stochastic gradient descent) combined with other techniques (such as batch normalization and momentum) to enhance the algorithm's efficiency (Kim et al., 2023; Zhang et al., 2024; Alonso-González et al., 2023; Ho et al., 2022). These advances in deep learning algorithm optimization will redefine entire industries and enable even more fundamental applications of this powerful technology.

3 Proposed Model

A. Construction Diagram

❖ Softmax

The softmax is a mathematical operation frequently used in machine learning and deep learning to convert the scores at the last layer of your network into probabilities. It accepts an array of real numbers

and applies the softmax function (also known as normalized exponential) to calculate the probability distribution. By the end, we will have an output vector whose elements are between 0 and 1, and the sum of its elements will equal 1. Before we begin learning about softmax, let me introduce you to the concept of probability distribution. A probability distribution is a function representing the likelihood that a product will pass at a given root-mean-square (RMS) value. Figure 1 Shows the construction diagram.

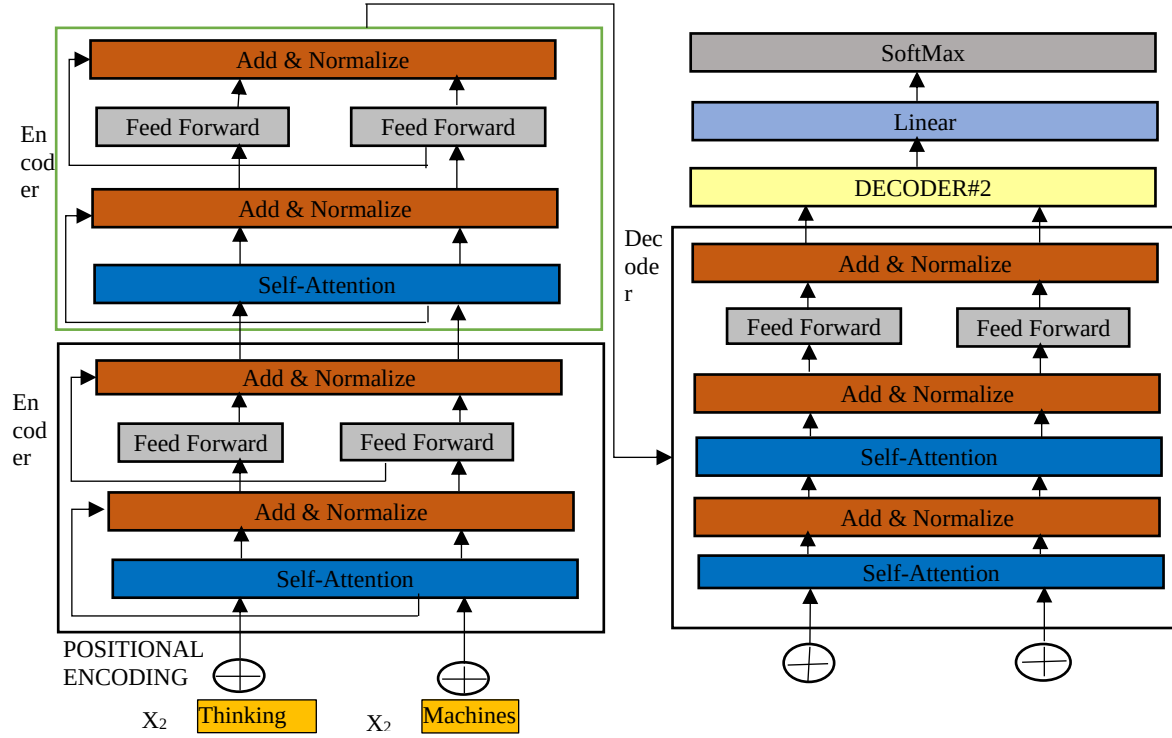


Figure 1: Construction Diagram

In a neural network, the output layer typically consists of some nodes that may correspond to a class or a category. These nodes will have a final output after the input has been propagated throughout the entire network. However, such output values are not probabilities; thus, they do not represent the probability of belonging to a specific class. This is where you need Softmax.

❖ Linear

Linear is an operation or function whose graph fulfills a straight line or is right of the relation. i.e., the out of the operation is linear in the in of the operation and with a constant derivative. The graph, in fact, is also a straight line. In essence, the Linear operation is just a multiplication and addition. It receives a single input and multiplies it by a constant, which is referred to as a slope or rate of change.

Formally, given a data matrix $Y \approx VU$, NMF consists in factorizing the matrix y

$$Y \approx VU^w \quad (1)$$

by minimizing the following objective function Φ :

$$\Phi = \frac{1}{2} \|Y - VU^w\| \quad (2)$$

In this case, the squared Euclidean distance is represented by the objective function Φ , which aims to minimise the error of the reconstruction of the original matrix X by the product UV . The following is a possible rewrite of the objective function:

$$\begin{aligned} \Phi &= \frac{1}{2} \text{tr} \left((Y - VU^T)(Y - VU^w)^w \right) \\ &= \frac{1}{2} \text{tr} (YY^w - 2WUV^w + VU^wUV^w) \\ &= \frac{1}{2} \left(\text{tr}(YY^w) - 2\text{tr}(YUV^w) + \text{tr}(VU^wUV^w) \right) \end{aligned} \quad (3)$$

This is the amount by which the input must change for the given output to be generated. The operation is a fundamental element in machine learning and data analysis. It is a method used to develop models that can perform a simple task – predict future values based on the dependence or relationship between variables. For instance, it can be used to illustrate a company's sales, depending on how much it spends on advertising or the impact of education on its earnings.

❖ Encoder

An Encoder is a device or software that converts an input signal into a code or a specific format. It is a fundamental building block of many kinds of devices, such as the telephone, music and video players, and television. The primary task of an Encoder is to compress the input signal, minimizing its size while preserving important characteristics of the input media. This compression is obtained by digitalizing the input signal, which the electronics can easily transmit, store, and process.

update algorithm to find a local minimum of the objective function Φ as follows:

$$V_{ji}^{w+1} = v_{ji}^w \frac{(YU)_{ji}}{(VU^wU)_{ji}} \quad (4)$$

$$u_{ji}^{w+1} = u_{ji}^w \frac{(Y^wV)_{ji}}{(UV^wV)_{ji}} \quad (5)$$

That being said, there are multiple ways to minimise the objective function Φ . In addition, and will constitute a solution for any positive diagonal matrix if and are the answers to.

$$v_{ji} = \frac{v_{ji}}{\sqrt{\sum_j v_{ji}^2}} \quad (6)$$

$$u_{ji} = u_{ji} \sqrt{\sum_j v_{ji}^2} \quad (7)$$

There are several steps in encoding, including sampling, quantization, and coding. Encoding is essentially sampling – the analog input signal is converted into discrete samples. These are samples of

the amplitude of the input signal at a given time. The number of such samples is determined by the sampling rate used to control the quality of the encoded signal.

❖ **Decoder**

A key element in digital implementations -by which encoded data is mapped to its translated data output. In the decoders, structurally, one receives an input code and several bits and generates an output that corresponds to the received code. The input code can be multibit but is parametric in a binary code, meaning that only one of two possible values (0 or 1) can be present.

As a result, a linear combination of the columns of, weighted by the components of, approximates each data vector.

$$e_{\theta}(Y) = m(Ty + a) \quad (8)$$

$\theta = \{T, a\}$ are the parameter set, where T is matrix and a is an offset vector of dimensionality.

The decoder checks the input code against a predetermined set of codes, known as the truth table, which contains all input combinations and their associated outputs. The decoder will be actuated based on how closely the input code matches the entries in the truth table. For instance, if the given code is 001, then the decoder output is the output represented by the row in the table that has 001 in the first three entries.

❖ **Encoder-Decoder Attention**

The encoder-decoder attention mechanism is a crucial component of an encoder-decoder network, which has achieved considerable success in sequence-to-sequence learning, including machine translation, text summarization, and speech recognition, among other applications. It allows the decoder to focus on pertinent parts of the input sequence while producing an accurate output sequence. The and the decoder in the Encoder-Decoder Attention are the two key components. Encoder: This is where the input sequence - a sentence here - is converted to an abstract, fixed-length vector. The decoder transforms this vector into the output sequence. The encoder-decoder Attention operation is also known as the encoding phase. During the encoding phase, the input sequence passes through the encoder, and on the other side, we obtain a collection of hidden states. The hidden states contain information from the input sequence and help the decoder better understand the input.

❖ **Self-Attention**

It's the self-attention, or intra-attention, mechanism in last year's deep learning architectures and throughout natural language processing (NLP) these days. It is a process of allowing the neural network to weigh different parts of the input sequence when focusing on the sequence itself. The objective of self-attention is, of course, to relate the various elements in a sequence to one another. This allows the neural network to prioritize the input sequence based on semantically relevant elements rather than assigning a strict ordering to every element within the input.

The mapping $h\theta$ is called the decoder and can be written as follows:

$$h\theta'(x) = m(T'x + a) \quad (9)$$

It can be understood as the parameters of a distribution that, with a high likelihood of producing x , results in a reconstruction error that needs to be minimised:

$$K(y, z) \propto -\log r(y|z) \quad (10)$$

Self-attention is quite simple. When you get down to it, you take one element and compare it to every other component of the sequence. The attention weights introduce this by allowing the different parts to consider one another. Note that these weights are the learning parameters of self-attention and are updated during training, which is crucial for the overall performance of self-attention.

❖ Positional Encoding

It is also important for natural language processing tasks, such as machine translation and text classification. Position encoding. This is encoded in the word or token vector of this word. This is crucial, as otherwise, the model would not be able to account for words that share a token but appear at different positions in a sentence. Positional encoding enables the model to determine the position of each word within a sentence; therefore, positional encoding is regarded as a key component of the entire seq-to-seq process. This is because standard neural network models for text generation, such as RNN and CNN, don't have the feature of learning sequential or positional information. For positional encoding, it's common to add a vector for the position to the original word vector. This positional embedding vector is calculated using a function for the position of this word in the sentence.

B. Functional Working Model

❖ Conv

Convolution (Conv) is an essential operation in deep learning used to extract features from data. It is widely used in CNN models for applications such as image and speech recognition, natural language processing, and others. Intuitively, Convolution consists of sliding a filter over an input feature map (or input image). The kernel filter is comprised of a small matrix of weights that is dragged over the input feature map. The element-wise product of the kernel filter with the input feature map results is summed to produce a single output value. The Conv operation is a series of steps.

Next, the encoding step of each layer is executed in forward order to determine the encoding step for the stacked auto-encoder. This is done as follows:

$$b^{(k)} = e\left(z^{(k)}\right) \quad (11)$$

$$z^{(k+1)} = T^{(k,1)}b^{(k)} + b^{(k,1)} \quad (12)$$

In our work, we classify behaviours using a softmax classifier. The softmax classifier has the following formal definition:

$$\text{softmax}(z)_j = \frac{\exp(z_j)}{\sum_{k=1}^D \exp(z_k)} \quad (13)$$

where D is the number of classes and represents the class-corresponding element of the input to softmax.

$$x^\Lambda = \sigma\left(T^w Y + a_p\right) \quad (14)$$

where x^Λ stands for the input vector, signifies the weight vector, and represents the activation function.

❖ Concatenation

This implies that the resultant string includes all the characters from both strings in the order in which they were combined. Concatenation: The simplest use of concatenation is adding two strings of text together (this usually means combining words or phrases). So, concatenating "Hello" and "World" would give us "HelloWorld." This small utility function enabled developers to DRY out their code and avoid copying and pasting strings all over the place. It is also applied in more advanced content, including generating strings dynamically or working with data from a database.

"Maxpool" is short for maximum pooling, which can be found in convolutional neural networks (CNNs), a type of artificial neural network used for image recognition. Maxpool is a pooling operation that reduces the input volume in size while preserving the important idea and usually operates between convolutional layers. Before discussing pooling, it is essential to understand how a max pool works. Pooling is a mechanism that shrinks the size of input data by performing certain mathematical operations

on a portion of the input. This facilitates the reduction of spatial dimensions by retaining only important features, thereby decreasing the computational complexity of the network.

❖ ReLu:

ReLU (Rectified Linear Unit) activation functions are widely used in deep learning. It is a relatively straightforward yet impactful feature of neural networks that introduces non-linearity and enables the teaching of higher-order higher-order relationships between input and output data. The mathematical representation of ReLu can be expressed as $f(x) = \max(0, x)$, where x is the input and $f(x)$ is the output.

The mean square error's mathematical representation is provided as follows:

$$MSE = \frac{1}{M} \sum_{j=1}^M (\rho^{\text{exp}} - \rho^{\text{db}})^2 \quad (15)$$

A P value close to 1 indicates a higher association. The outputs and targets have a greater linear relationship than anticipated. The following is the regression values' mathematical representation:

$$P^2 = \frac{\sum_{j=1}^M [(\rho^{\text{exp}} - \rho')^2 - (\rho^{\text{exp}} - \rho^{\text{db}})^2]}{\sum_{j=1}^M (\rho^{\text{exp}} - \rho')^2} \wedge 2. \quad (16)$$

The maximum solar power plant power depends linearly on the performance ratio, which is given by

$$RP = R_j / R_{\text{nom}} * H_{\text{STC}} / g_i \quad (17)$$

Reactive power in an electrical energy distribution system that functions linearly in the sinusoidal signal mode is determined using the following ratio:

$$P = J \times V \times \sin \varphi \quad (18)$$

Given the nonharmonic signal's influence on the system's operating mode, the effective current and voltage values in the electrical network are provided as

$$V = \sum_{l=1}^L V_l \sin(2\pi l f_0 t - \theta_l) \quad (19)$$

$$J = \sum_{l=1}^L J_l \sin(2\pi l f_0 t - \psi_l)$$

Here, θ_l denotes the starting phases of the signal, J_l is the current harmonic value, f_0 indicates the frequency, and l represents the harmonic number.

$$p_r = \frac{\sum_{j=1}^m (y_j - \bar{y})(x_j - \bar{x})}{\sqrt{\sum_{j=1}^m (y_j - \bar{y})^2} \sqrt{\sum_{j=1}^m (x_j - \bar{x})^2}} \quad (20)$$

where p_r is the Pearson correlation coefficient, m is the variable's length, and $\bar{y}$ and $\bar{x}$ are the sample means, respectively.

That's right, ReLu is a function that takes a scalar value as input and returns the same value if it's positive or 0 if it's negative. One of the reasons to like ReLu is that it is nothing but loose while also being computationally cheap. ReLU does not have exponential operations, unlike Sigmoid or Tanh. In

contrast, the simple threshold operator does not require such computations and is much faster to compute, particularly for deep neural networks with many layers.

C. Operating Principle

❖ Unmanned Ship

Definition In this context, an uncrewed ship (also known as an autonomous ship) is a ship that is capable of operating and navigating without human intervention on, in, or under its surface. All these ships are high-tech, as they are guided by complex systems that enable them to perform numerous tasks and operations without human intervention. Sensors, control systems, and communications are the key elements of an uncrewed ship. All of these systems play their part in allowing the boat to sense and understand its surroundings, decide what to do, and take the necessary actions to get there. Sensors are key for an uncrewed boat, especially for monitoring the ship's surroundings.

$$r_m = 1 - \frac{\left(6 \sum_{j=1}^m (P(y_j) - P(x_j))^2\right)}{(m(m^2 - 1))} \quad (21)$$

where is the variable's length, and are the two variables' ranks in their corresponding column vectors.

$$p_d = \text{corry}(x, y_1, \dots, y_m) = \sqrt{\frac{\sum_{j=1}^m (\hat{x}_j - \bar{x})^2}{\sum_{j=1}^m (x_j - \bar{x})^2}} \quad (23)$$

where is the mean value of and is the linear regression of to.

The following is how the neural network with full connectivity is calculated:

$$\begin{aligned} z_j^{(l+1)} &= t_j^{(k+1)} x^k + a_j^{(k+1)} \\ x_j^{(k+1)} &= e(z_j^{(k+1)}) \end{aligned} \quad (24)$$

$$p_j^{(k+1)} \sim \text{Bernoulli}(r),$$

$$\begin{aligned} x^{(k)} &= p^{(k)} * x^{(k)} \\ z_j^{(k+1)} &= t_j^{(k+1)} x^{(k)} + a_j^{(l+1)} \\ x_j^{(k+1)} &= e(z_j^{(k+1)}) \end{aligned} \quad (25)$$

These sensors, which include cameras, radar, lidar, and sonar, constantly scan the ship's surroundings and gather information about the boat's location, speed, and potential hazards in its path. This data is then pumped into the ship's control systems, which tap into an arsenal of algorithms and artificial intelligence not only to read that data but also to make decisions based on it.

❖ Environment

Environment is a fundamental term in computer science (or programming), referring to a data structure that represents variables with their associated values, which are available to a running program. It's an important phase of execution, providing the application with a place where it can sit, be isolated, and be

controlled. Here, 'environment' refers to the specific context in which the computer system operates and is connected at a given time, encompassing hardware, software, and system assets. Figure 3: Shows the operational flow diagram.

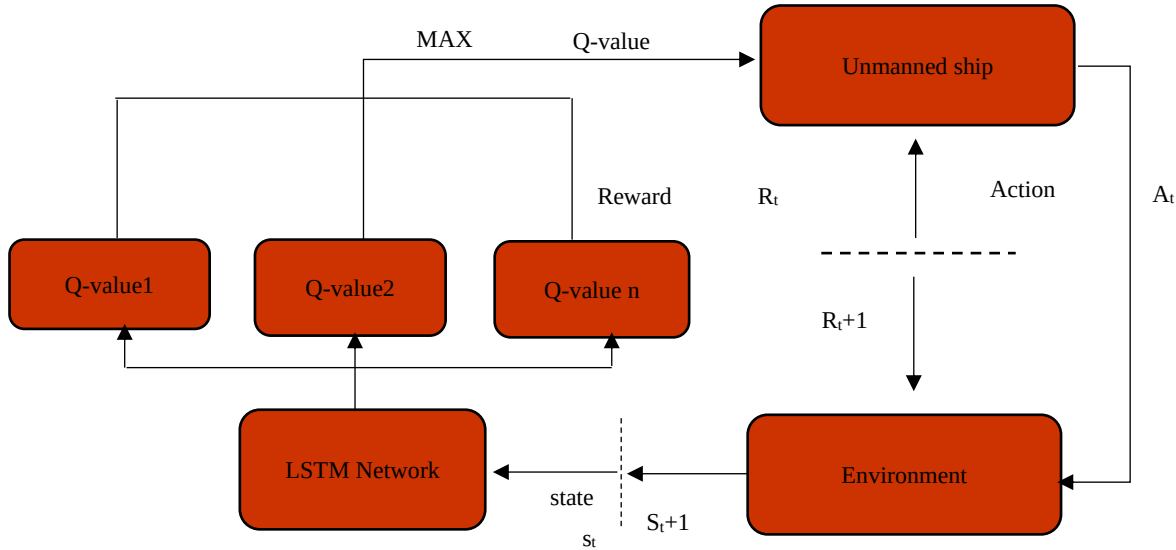


Figure 3: Operational flow diagram

The environment is one of the fundamental building blocks in a system, acting as a technology bridge between the program and the bare metal and also serving as a translator between the two different technologies. When you run a program, the operating system creates an environment in which it runs. One of the main operations that the above system's resource management and dispensation environment undertakes is the dynamic allocation of shared memory segments on the shared memory devices, which involves either dynamic or static allocation of shared memory contracts by the applications. These resources can include memory, disk, and CPU. It would ensure that the programs receive the correct resources, allowing them to run as needed without interfering with other programs that occur in the operating system.

❖ LSTM Network

An LSTM (Long Short-Term Memory) network is a type of recurrent neural network used in the field of computer science. It is very popular in NLP, speech recognition, and other sequential data tasks. LSTM was explicitly designed to carry and store information over a long period, making it suitable for capturing patterns in a long sequence of data. LSTM has three types of gates, including the input gate, forget gate, and output gate. They determine what information should pass through the network and what should be discarded and/or remembered – this is the input gate, and they decide which data traveling from left to right the network should track. It passes the new input and the previous cell state as inputs and then calculates an input modulation value, which determines how much of the new input should be allowed to flow into the cell state.

❖ Reward

Reward is also used as an operation in many domains (psychology (in behaviorism or behavior analysis), education, and game theory) to reinforce behavior, making it more mentionable, desirable, and repeatable and to encourage its appearance immediately or to appear more often. This is an operation

in which an individual is given a positive consequence or reward contingent upon a certain response or behavior. It's the equivalent of telling someone "good job" or "well done" to praise and encourage a particular behavior. Reward as a source for Reinforcement Reinforcement's main purpose is to potentiate and maintain behavior, and Reward serves as a basis for it.

To realise the shielding of neurons assigned as 0, the Bernoulli function's job is to make the value 1 or 0 with probability.

The following is the calculation equation for the composite correlation coefficient for a characteristic vector of any two sensors.

$$p_m = \begin{cases} \frac{\sum_{j=1}^m (y_i - \bar{y})(y_j - \bar{y})}{\sqrt{\sum_{j=1}^m (y_j - \bar{y})^2} \sqrt{\sum_{j=1}^m (y_i - \bar{y})^2}}, & j > i \\ \text{corr}(y_j, y_1, \dots, y_{j-1}, y_{j+1}, \dots, y_m), & j = i \\ 1 - \frac{\left(6 \sum_{j=1}^m (P(y_j) - P(y_i))^2\right)}{(m(m^2 - 1))}, & j < i \end{cases} \quad (26)$$

Thus, the initial step in visualising the composite correlation coefficient matrix is image generation. The two-dimensional matrix is converted into an 8 bit grayscale image in this paper in the following manner:

$$h = \left[\frac{h - h_{\min}}{h_{\max} - h_{\min}} \right] \times 255, \quad (27)$$

where g is the grey value of the associated picture pixel after transformation, xmax and xmin are the maximum and minimum values of the elements, and x represents the element in the composite correlation coefficient matrix.

The learning rate is initially fixed at 0.001. The validation set is used to assess the loss and precision of the current model at the conclusion of each training epoch.

$$rl^* = rl * 0.1. \quad (28)$$

This is because when we receive a treatment, dopamine is released in the brain, a neurotransmitter associated with feelings of pleasure and motivation. There are several moving parts to "Reward." The first is to reinforce the response. This might be a particular behavior, such as studying for a test, or more general, like being kind to others. The point is that the behavior is well-specified, observable, and rewarding.

❖ Action

The term "Action" is commonly used across various disciplines, including computer science, psychology, and philosophy. However, it usually implies making something happen or effecting a change. In computer science, an action is typically something done by a computer program in response to user input. The grey histogram information is calculated using Eq. (9), and the formulas for the histogram features are shown below

$$X(e) = \frac{F(e)}{V}, e = 0, 1, \dots, M, \quad (29)$$

where Tre denotes the total number of pixels in the image, N is the maximum value of the grey level in the image, g is the grey level, and P(g) is the number of pixel points in the image with a grey level of g.

$$\bar{y}_j = \sum_{j=1}^W y_j / W \quad (30)$$

corresponds to the average value across instances, whereas represents the monitoring value at the instance.

$$Y'_j = \text{diff}(\log(y_j)) \quad (31)$$

The $\text{diff}(\log(y_j))$ function is a mathematical tool for calculating the derivative of a given function.

This can be as simple as pressing a button or as intricate as performing a set of algorithms that solve a mathematical problem and how we interact with them as users. The way action works in an interaction includes many things, from the user thinking, "I want to close this thing using that other one on the side over there," to them waving their fingers in the right spot as you parse their movement and display it on-screen. This can be achieved through various means, including pressing a button, entering a command, or making a verbal request using voice recognition. After understanding what the user wants to do, the system determines the appropriate response. It does so by taking into account several aspects of the system's current situation, as well as how users would like the system to behave.

4 Result and Discussion

The proposed model, i.e., NARMEX (Non-Autonomous Rolling Momentum with Exponentially Weighted Average), has been compared with the current LBFGS (Limited-memory Broyden–Fletcher–Goldfarb–Shanno), PEGASUS (Preconditioned Gradient Ascent), and ADAGRAD-SGD (Adaptive Gradient Descent with AdaGrad)

4.1. Accuracy

It represents the proportion of correctly predicted tear data by the deep learning algorithm. Precision is crucial for enabling the algorithm to process tear sensor data effectively. Table 2 Comparison of Accuracy between Existing and Proposed Model Figure 4.

Table 2: Comparison of Accuracy (in %)

No. of Inputs	LBFGS	PEGASUS	ADAGRAD	NARMEX
100	60.51	59.43	35.50	64.47
200	59.02	57.46	33.08	62.27
300	58.22	56.33	32.67	61.47
400	55.89	55.12	31.07	60.80
500	54.88	54.75	28.75	59.37

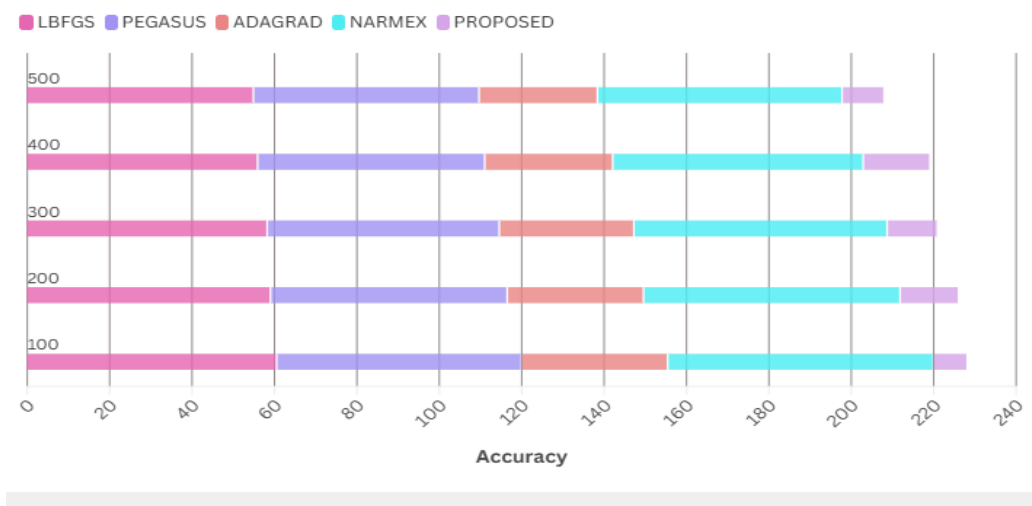


Figure 4: Computation of the Accuracy

4.2. Processing Speed

The real-time capability of tear sensor data processing by deep learning is also an important technical performance index. High processing speed is significant in derisory time statistics and for real-time answers. Table 3 demonstrates the comparison of the Processing Speed of the former and latter models. Figure 5.

Table 3: Comparison of Processing Speed (in %)

No. of Inputs	LBFGS	PEGASUS	ADAGRAD	NARMEX	NARMEX
100	63.51	77.43	43.50	69.47	63.51
200	62.02	75.46	41.08	67.27	62.02
300	61.22	74.33	40.67	66.47	61.22
400	58.89	73.12	39.07	65.80	58.89
500	57.88	72.75	36.75	64.37	57.88

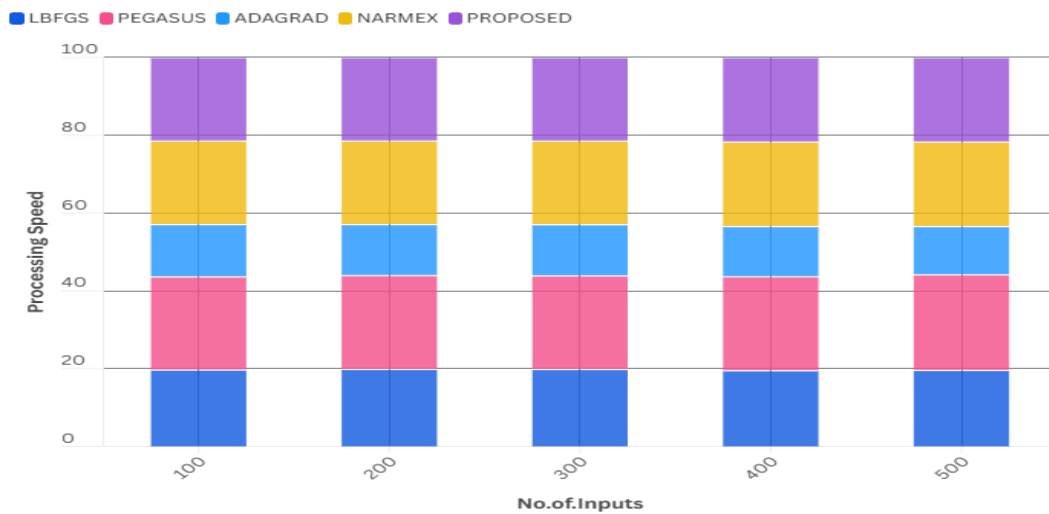


Figure 5: Computation of the Processing Speed

4.3. Model Complexity

The performance of the algorithm can be affected by the complexity of the deep learning model. An algorithm should be developed to strike a balance between accuracy and complexity, allowing tear data to be analyzed efficiently. Table 4 presents the Model Complexity Comparison of existing and proposed models Figure 6 and 7.

Table 4: Comparison of Model Complexity (in %)

No. of Inputs	LBFGS	PEGASUS	ADAGRAD	NARMEX
100	71.51	82.43	48.50	74.47
200	70.02	80.46	46.08	72.27
300	69.22	79.33	45.67	71.47
400	66.89	78.12	44.07	70.80
500	65.88	77.75	41.75	69.37

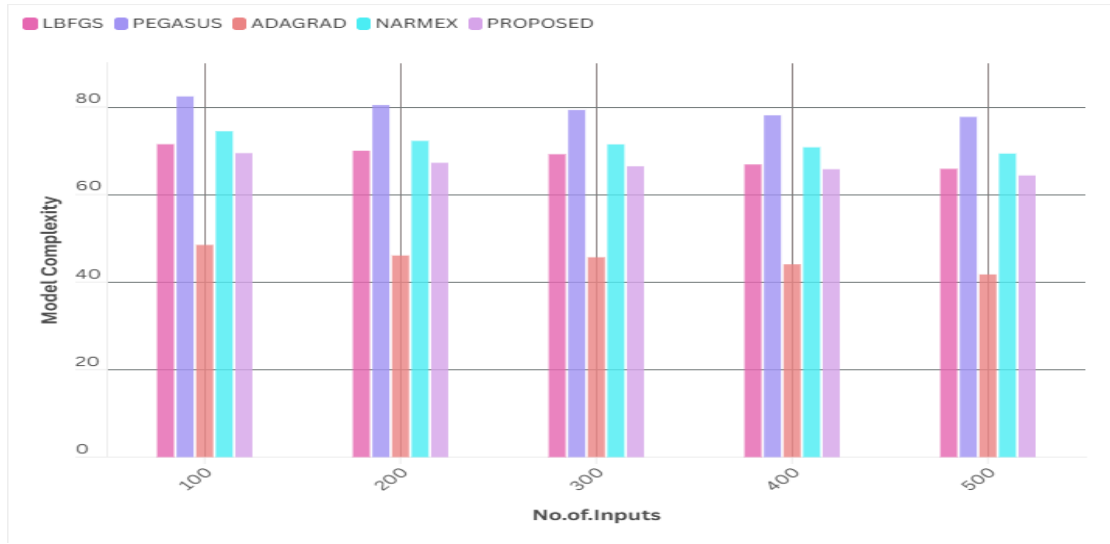


Figure 6: Computation of the Model Complexity

4.4. Generalization

Deep learning models should be well-generalized on novel test data rather than merely memorizing the training data. The algorithm needs to work across various environments to accurately model the proposed one (in terms of Generalization) Table 5.

Table 5: Comparison of Generalization (in %)

No. of Inputs	LBFGS	PEGASUS	ADAGRAD	NARMEX
100	79.51	85.43	57.50	81.47
200	78.02	83.46	55.08	79.27
300	77.22	82.33	54.67	78.47
400	74.89	81.12	53.07	77.80
500	73.88	80.75	50.75	76.37

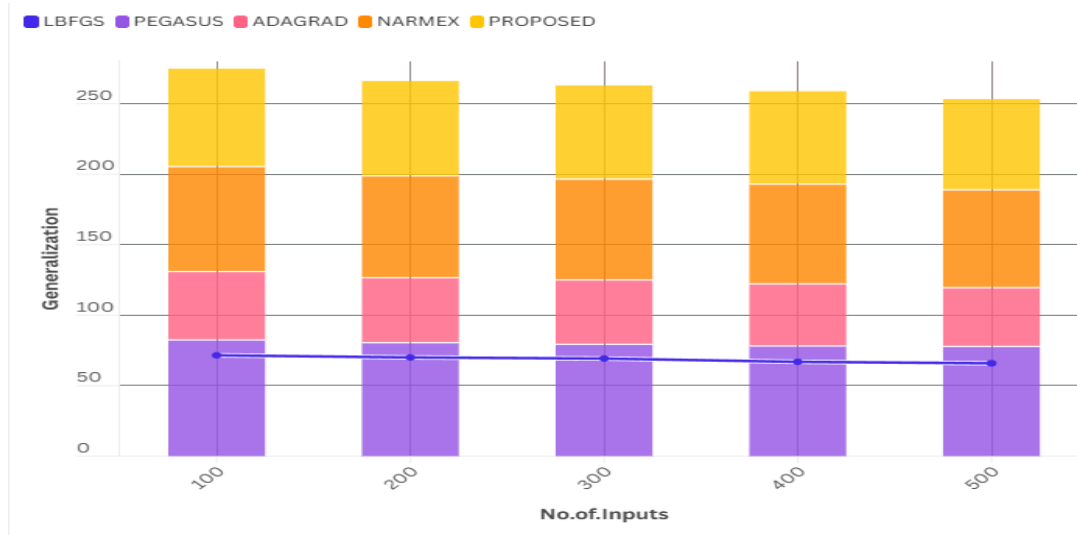


Figure 7: Computation of the Generalization

5 Conclusion

Therefore, the deep learning algorithms applied to the analysis of tear sensor data should be algorithmically refined to represent the tear more accurately and analyze its data. There is a wealth of valuable information in tears that can reveal what is happening with the eye, and deep learning enables us to analyze the data extracted from tears much faster and more accurately. The potential of deep learning algorithms, via the application of neural or convolutional neural network techniques, is to distill the rich data of the gradient tear and generate a 'good' qualitative or quantitative data output: useful, stable, and reliable. Besides the above, through Algorithmic, we are optimizing these algorithms to return a better result by running faster, which makes it possible to use them in real-time scenarios. Additionally, mitigating deep learning algorithms for tear sensor data analysis can improve not only diagnostic accuracy but also be beneficial in other ways. Moreover, it can aid in the early detection and prompt treatment of ocular diseases, resulting in improved patient outcomes and quality of life (QoL). However, the field is still confronted with unsolved problems, such as privacy and interpretability issues with the algorithms. We also need to continue to ensure patient privacy and transparency to avoid the black-boxing of algorithms.

References

- [1] Abidi, M. H., Mohammed, M. K., & Alkhalefah, H. (2022). Predictive maintenance planning for industry 4.0 using machine learning for sustainable manufacturing. *Sustainability*, 14(6), 3387. <https://doi.org/10.3390/su14063387>
- [2] Albert Mayan, J., Nayak, P. P., Ganesh, D., Agarwal, T., Sharma, N., Srinath, G., & Kaushik, N. (2025). Computer vision-based system for tracking and monitoring aquatic animals. *International Journal of Aquatic Research and Environmental Studies*, 5(1), 23-29. <https://doi.org/10.70102/IJARES/V5I1/5-1-03>
- [3] Alonso-González, M., Díaz, V. G., Pérez, B. L., G-Bustelo, B. C. P., & Anzola, J. P. (2023). Bearing fault diagnosis with envelope analysis and machine learning approaches using CWRU dataset. *IEEE Access*, 11, 57796-57805. <https://doi.org/10.1109/ACCESS.2023.3283466>

- [4] Amethiya, Y., Pipariya, P., Patel, S., & Shah, M. (2022). Comparative analysis of breast cancer detection using machine learning and biosensors. *Intelligent Medicine*, 2(2), 69-81. <https://doi.org/10.1016/j.imed.2021.08.004>
- [5] Binny, S., & Maran, P. S. (2025). An Integrated CNN-RNN Framework for Enhanced Rheumatoid Arthritis Detection and Diagnosis from Medical Imaging. *Journal of Internet Services and Information Security*, 15(2), 103-124. <https://doi.org/10.58346/JISIS.2025.I2.008>
- [6] Boopathy, E. V., Shanmugasundaram, M., Vadivu, N. S., Karthikkumar, S., Diban, R., Hariharan, P., & Madhan, A. (2024). Lorawan Based Coalminers Rescue and Health Monitoring System Using IOT. *Archives for Technical Sciences*, 2(31), 213-219. <https://doi.org/10.70102/afts.2024.1631.213>
- [7] Djeddi, A. Z., Hafaifa, A., Hadroug, N., & Iratni, A. (2022). Gas turbine availability improvement based on long short-term memory networks using deep learning of their failures data analysis. *Process Safety and Environmental Protection*, 159, 1-25. <https://doi.org/10.1016/j.psep.2021.12.050>
- [8] El Barche, F. Z., Benyoussef, A. A., El Habib Daho, M., Lamard, A., Quelled, G., Cochener, B., & Lamard, M. (2024). Automated tear film break-up time measurement for dry eye diagnosis using deep learning. *Scientific Reports*, 14(1), 11723. <https://doi.org/10.1038/s41598-024-62636-5>
- [9] Garaszczuk, I. K., Romanos-Ibanez, M., & Consejo, A. (2024). Machine learning-based prediction of tear osmolarity for contact lens practice. *Ophthalmic and Physiological Optics*, 44(4), 727-736. <https://doi.org/10.1111/opo.13302>
- [10] Ho, T. T., Kim, G. T., Kim, T., Choi, S., & Park, E. K. (2022). Classification of rotator cuff tears in ultrasound images using deep learning models. *Medical & Biological Engineering & Computing*, 60(5), 1269-1278. <https://doi.org/10.1007/s11517-022-02502-6>
- [11] Kim, H., Lee, S., Lee, K. W., Kim, E. S., Kim, H. M., Im, H., ... & Kim, E. (2023). Indolizine-based fluorescent compounds array for noninvasive monitoring of glucose in bio-fluids using on-device machine learning. *Dyes and Pigments*, 215, 111287. <https://doi.org/10.1016/j.dyepig.2023.111287>
- [12] Kumar, A., Sharma, K., & Sharma, A. (2021). Genetically optimized Fuzzy C-means data clustering of IoMT-based biomarkers for fast affective state recognition in intelligent edge analytics. *Applied Soft Computing*, 109, 107525.
- [13] Kumar, P., Saradha, S., Meena, M., Vijayakumar, S., & Pushpalatha, N. (2025). 4 The Resilience of Artificial Intelligence in the Mechatronics Sector. *Handbook of AI-Based Mechatronics Systems and Smart Solutions in Industrial Automation*.
- [14] Lee, K., Kim, J. Y., Lee, M. H., Choi, C. H., & Hwang, J. Y. (2021). Imbalanced loss-integrated deep-learning-based ultrasound image analysis for diagnosis of rotator-cuff tear. *Sensors*, 21(6), 2214. <https://doi.org/10.3390/s21062214>
- [15] Mousavizadegan, M., Firoozbakhtian, A., Hosseini, M., & Ju, H. (2023). Machine learning in analytical chemistry: From synthesis of nanostructures to their applications in luminescence sensing. *TrAC Trends in Analytical Chemistry*, 167, 117216. <https://doi.org/10.1016/j.trac.2023.117216>
- [16] Ngwa, P., & Ngaruye, I. (2023). Big data analytics for predictive system maintenance using machine learning models. *Advances in data science and adaptive analysis*, 15(01n02), 2350001. <https://doi.org/10.1142/S2424922X23500018>
- [17] Odimarha, A. C., Ayodeji, S. A., & Abaku, E. A. (2024). Machine learning's influence on supply chain and logistics optimization in the oil and gas sector: a comprehensive analysis. *Computer Science & IT Research Journal*, 5(3), 725-740. <https://doi.org/10.51594/csitrj.v5i3.976>
- [18] Selvaraj, Y., & Selvaraj, C. (2022). Proactive maintenance of small wind turbines using IoT and machine learning models. *International Journal of Green Energy*, 19(5), 463-475. <https://doi.org/10.1080/15435075.2021.1930004>

- [19] Sethi, R., & Soman, N. (2022). Secured Multi-Party Computations for Privacy-Preserved Medical Data Analysis. *International Academic Journal of Science and Engineering*, 9(3), 31–35. <https://doi.org/10.71086/IAJSE/V9I3/IAJSE0926>
- [20] Sherlin, D., & Nikila, I. (2022). Detection and Diagnosis of Brain Tumor Using Wavelet Transform and Machine Learning Model. *International Academic Journal of Innovative Research*, 9(1), 01-05.
- [21] Shimizu, F. M., de Barros, A., Braunger, M. L., Gaal, G., & Riul Jr, A. (2023). Information visualization and machine learning driven methods for impedimetric biosensing. *TrAC Trends in Analytical Chemistry*, 165, 117115. <https://doi.org/10.1016/j.trac.2023.117115>
- [22] Sircar, A., Yadav, K., Rayavarapu, K., Bist, N., & Oza, H. (2021). Application of machine learning and artificial intelligence in oil and gas industry. *Petroleum Research*, 6(4), 379-391. <https://doi.org/10.1016/j.ptlrs.2021.05.009>
- [23] Sun, J., Wang, L., & Razmjoooy, N. (2023). Anterior cruciate ligament tear detection based on deep belief networks and improved honey badger algorithm. *Biomedical Signal Processing and Control*, 84, 105019. <https://doi.org/10.1016/j.bspc.2023.105019>
- [24] Tan, W., Sarmiento, J., & Rosales, C. A. (2024). Exploring the Performance Impact of Neural Network Optimization on Energy Analysis of Biosensor. *Natural and Engineering Sciences*, 9(2), 164-183. <https://doi.org/10.28978/nesciences.1569280>
- [25] Wang, C., He, T., Zhou, H., Zhang, Z., & Lee, C. (2023). Artificial intelligence enhanced sensors-enabling technologies to next-generation healthcare and biomedical platform. *Bioelectronic Medicine*, 9(1), 17. <https://doi.org/10.1186/s42234-023-00118-1>
- [26] Xue, Y., Yang, S., Sun, W., Tan, H., Lin, K., Peng, L., ... & Zhang, J. (2024). Approaching expert-level accuracy for differentiating ACL tear types on MRI with deep learning. *Scientific Reports*, 14(1), 938. <https://doi.org/10.1038/s41598-024-51666-8>
- [27] Yang, A. M., Zhi, J. M., Yang, K., Wang, J. H., & Xue, T. (2021). Computer vision technology based on sensor data and hybrid deep learning for security detection of blast furnace bearing. *IEEE Sensors Journal*, 21(22), 24982-24992. <https://doi.org/10.1109/JSEN.2021.3077468>
- [28] Zhang, M., Huang, C., & Druzhinin, Z. (2024). A new optimization method for accurate anterior cruciate ligament tear diagnosis using convolutional neural network and modified golden search algorithm. *Biomedical Signal Processing and Control*, 89, 105697. <https://doi.org/10.1016/j.bspc.2023.105697>
- [29] Zhang, S., Suresh, L., Yang, J., Zhang, X., & Tan, S. C. (2022). Augmenting sensor performance with machine learning towards smart wearable sensing electronic systems. *Advanced Intelligent Systems*, 4(4), 2100194. <https://doi.org/10.1002/aisy.202100194>
- [30] Zhao, Y., Qiu, J., Li, Y., Khan, M. A., Wan, L., & Chen, L. (2024). Machine-learning models for diagnosis of rotator cuff tears in osteoporosis patients based on anteroposterior X-rays of the shoulder joint. *SLAS technology*, 29(4), 100149. <https://doi.org/10.1016/j.slats.2024.100149>

Authors Biography



Dr. Sarbeswar Hota is an Associate Professor in the Department of Computer Applications at Siksha 'O' Anusandhan (Deemed-to-be University), Bhubaneswar. His research interests include data mining, artificial intelligence, cloud computing, and cybersecurity. He has published several research papers in reputed national and international journals and conferences. Dr. Hota is also actively involved in guiding postgraduate students and fostering interdisciplinary collaborations in computational and applied computer science.



Dr. Abhiraj Malhotra is associated with the Centre of Research Impact and Outcome at Chitkara University, Punjab. His professional focus lies in research analytics, institutional development, and innovation management. He contributes to projects enhancing the visibility and quality of academic research, emphasizing data-driven decision-making and research outcome evaluation. Mr. Malhotra also collaborates on initiatives supporting sustainable innovation and performance metrics in higher education.



Dr.R. Hannah Jessie Rani is an Assistant Professor in the Department of Electrical and Electronics Engineering at JAIN (Deemed-to-be University), Bangalore. Her teaching and research interests include power systems, control engineering, renewable energy technologies, and smart grid applications. She has authored and co-authored papers in peer-reviewed journals and actively participates in academic and industry collaborations focused on sustainable energy solutions.



Dr. Vijay Jagdish Upadhye is an Associate Professor in the Department of Microbiology and a member of the Research and Development Cell at Parul University, Gujarat. His expertise spans environmental microbiology, medical microbiology, and biotechnological applications. Dr. Upadhye has been actively involved in research on microbial diversity, antimicrobial resistance, and bio-innovation. He is dedicated to promoting research-based learning and capacity building in life sciences.



Prateek Aggarwal is affiliated with the Chitkara Centre for Research and Development, Chitkara University, Himachal Pradesh. His primary work focuses on research development, policy analytics, and outcome-based academic performance. He supports institutional projects that foster innovation ecosystems and strengthen research impact through quantitative assessment frameworks. Mr. Aggarwal also contributes to research management and coordination across interdisciplinary domains.



Dr. Awakash Mishra serves as a Professor at the Maharishi School of Engineering & Technology, Maharishi University of Information Technology, Uttar Pradesh. His academic and research expertise includes electrical and electronics engineering, automation, and sustainable energy systems. Dr. Mishra has published and presented extensively at national and international levels, contributing to advancements in applied engineering and academic leadership.